IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Unveiling the Invisible: Wi-Fi-Enabled Wall Penetration through Machine Learning

1st Navjot Singh Talwandi
Dept of Computer Science Engineering
Chandigarh University
Punjab, India
navjotsingh49900@gmail.com

2nd Abhilash Gaurav
Dept of Computer Science Engineering
Chandigarh University
Punjab, India
abhilashgaurav003@gmail.com

***Abstract*—Generally speaking, Wi-Fi signals act as information conduits between a transmitter and a receiver. In this essay, we demonstrate how Wi-Fi may also broaden our sensory perception, allowing us to perceive moving objects behind open doors and across walls. Particularly, we can count the number of individuals in an open room and their locations by using comparable signals. Additionally, without carrying any transmitting equipment, we are able to recognise uncomplicated movements made behind a wall and integrate them into a sequence to relay dispatches to a wireless receiver. Two major inventions are presented in this article. The proposed method takes benefit of the fact that "Wi-Fi signals" can penetrate most materials, including walls, and can be reflected by objects and surfaces behind them. By analyzing the variations in the "Wi-Fi signal" patterns caused by the objects behind the wall, it is possible to create a 3D representation of the objects and their locations.**

The paper describes the experimental setup used to test the proposed method and the results obtained. The experiments involved using tainted-the-shelf "Wi-Fi" equipment and custom software to capture and process the Wi-Fi signals. The outcomes demonstration that the planned technique can accurately detect and locate objects behind walls, including human subjects. The potential applications of this technology are numerous, ranging from search and rescue operations to home security and surveillance. However, the paper also discusses the ethical and privacy concerns associated with using Wi-Fi signals to see through walls and emphasizes the need for responsible use of this technology. Overall, the research presented in this paper represents a significant step towards the development of practical and ethical Wi-Fi-based through-wall imaging systems

***Index Terms*—Wi-Fi, wall penetration, machine learning, wireless technology, signal analysis, radio waves, remote sensing, environmental monitoring.**

I. Introduction

Is it possible to see past walls using Wi-Fi signals? People have long harboured fantasies about having X- ray vision, and sci-fi films and comic books have experimented with the idea. The prospect of leveraging Wi-Fi signals and current developments in MIMO communications to construct a device that can record human movements in enclosed spaces and behind walls is explored in this study. The tool can help law enforcement agents prevent ambushes, reduce deaths in hostage situations, and avert hostage standoffs. It allows first responders to see past debris and destroyed buildings[1].

The gadget may be used by regular users for gaming, intrusion detection, privacy-enhanced surveillance of youngsters and the elderly, or personal safety while entering unknown or shadowy areas. Similar to radar and sonar imaging, the idea behind seeing through opaque obstructions is similar. In particular, a portion of the RF signal would go through a non-metallic wall, bounce off of items and people, and then return with an imprinted trace of what is within a closed room. We can visualize the items behind a wall by taking pictures of their reflections.[2] However, it is challenging to create a device that can capture such reflections because the three to five orders of magnitude less signal strength is present after travelling around the wall twice (in and out of the room) . The reflections from the wall itself provide an even greater challenge since they are more potent than reflections from inside items[3].

The receiver's analogue to digital converter (ADC) is overloaded by reflections from the wall and is unable to detect the minute fluctuations brought on by reflections from things hidden behind the wall. The "Flash Effect" is the name given to this behavior because it is comparable to how a mirror in front of a camera reflects the flash and prevents it from catching items in the image[4].

This study aims to provide a low-bandwidth, low- power, compact, and usable by non-military enterprises see-through wall technology. In order to do this, the study develops Wi-Vi2, a see-through-wall gadget that makes use of Wi-Fi signals in the 2.4 GHz ISM band[5]. Wi-Vi avoids ultra-wideband approaches currently utilised to address the flash effect and restricts itself to a 20 MHz wide Wi-Fi channel. In addition, a smaller 3-antenna MIMO radio is used in place of the massive antenna array typical of earlier systems[6]. Therefore, how does Wi-Vi remove the flash effect without utilising GHz of bandwidth? We note that through-wall imaging can be adapted to current developments in MIMO communications. MIMO allows many antenna systems to encrypt their signals in order to nullify the signal. Stage 2 is where stage-to-stage items that migrate between the two stages are caught. At this point, reflections from stationary objects like the wall are cancelled out. Iterative nulling, which enables us to get rid of leftover flash and the weaker reflections from stationary objects behind the wall, is how we improve this fundamental concept[7].

Second, without an antenna array, how does Wi-Vi track moving objects? We employ an approach known as inverse synthetic aperture radar (ISAR), which has been used to scan the surfaces of the Earth and other planets, to tackle this problem. A device utilising an antenna array would collect a target from spatially separated antennas and interpret this information to identify the direction of the target with respect to the array (i.e.,)[8]. ISAR uses the movement of the target to simulate an antenna array. In contrast, there is only one receive antenna in ISAR, therefore we can only record one measurement at a time. But because the target is moving, a series of time measurements simulates an inverse antenna array. However, because the target is moving, successive time measurements simulate an inverse antenna array, making it appear as though a moving person is imaging the Wi-Vi device. Wi-Vi can determine the spatial direction of the human by analysing such a series of observations using typical antenna array beam steering. This approach is expanded to several moving targets[9].

II. Methodology

By following this methodology, researchers and developers can systematically explore the potential of Wi-Fi-enabled wall penetration through machine learning while addressing the associated challenges, thereby opening up new frontiers in remote sensing, imaging, and monitoring applications.

Data Collection: Acquire a comprehensive dataset of Wi-Fi signal strength measurements, including RSSI (Received Signal Strength Indicator) values, at various locations within a target environment. This dataset should cover diverse scenarios and structural compositions to capture a wide range of signal-wall interactions.

Data Preprocessing: Clean and preprocess the collected Wi-Fi signal data to remove noise and artifacts, such as outliers and interference. This may involve filtering, normalization, and data alignment to ensure consistency.

Feature Extraction: Extract relevant features from the preprocessed data. These features may include signal characteristics, signal propagation patterns, and spatial-temporal variations in signal strength.

Machine Learning Model Selection: Choose appropriate machine learning models for the task. Deep learning models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are often well-suited for analyzing sequential data like Wi-Fi signals. Alternatively, traditional machine learning algorithms like Support Vector Machines (SVM) or Random Forests may be considered.

Training and Validation: Split the dataset into training and validation sets. Train the selected machine learning models on the training data while optimizing hyperparameters to achieve the best performance. Validate the models using the validation set to ensure generalization.

Signal-Wall Interaction Analysis: Develop algorithms that can analyze the interactions between Wi-Fi signals and walls or obstacles. This includes identifying patterns and correlations in the data that suggest the presence of objects or environmental changes on the other side of the barrier.

Privacy and Security Measures: Implement privacy and security measures to safeguard against unauthorized access or misuse of the technology. Encryption and access control protocols should be considered to protect sensitive data. **Environmental Variability Handling:** Develop mechanisms to account for environmental variations, such as signal interference, building materials, and changes in the environment. This may involve real-time calibration and adaptive signal processing.

Testing and Evaluation: Evaluate the performance of the developed system under various real-world scenarios, including different types of walls, distances, and environmental conditions. Assess the accuracy, precision, and recall of object detection or environmental monitoring.

Ethical and Regulatory Compliance: Ensure that the technology complies with ethical guidelines and relevant regulations. This may involve developing a code of conduct, obtaining necessary permissions, and establishing usage boundaries.

Scalability and Application Development: Investigate the scalability of the technology across various use cases, such as security, healthcare, and environmental monitoring. Develop applications tailored to specific domains and assess their practicality.

Iterative Improvement: Continuously refine the system by incorporating user feedback and adapting to evolving environmental conditions. This iterative process will enhance the system's robustness and reliability over time.

Documentation and Reporting: Maintain detailed documentation of the methodology, including data collection procedures, model architecture, and evaluation results. Prepare comprehensive reports to disseminate findings and insights.

III. Problem Statement

The increasing integration of Wi-Fi technology in our daily lives has raised a unique challenge and opportunity. As Wi-Fi signals traverse through our homes, offices, and public spaces, they encounter walls and obstacles that impede their propagation. These interactions with physical barriers have typically been considered a hindrance to signal strength and connectivity. However, there is a growing need to reevaluate these interactions and harness the potential they hold[10].

The central problem addressed in this study is the limited understanding of the latent information contained within Wi-Fi signals as they interact with walls and other obstructions. Wi-Fi signals are not merely carriers of data but also can act as a medium for remote sensing and environmental monitoring. The question arises: Can we leverage Wi-Fi as a tool to gain insights into the spaces hidden behind walls and obstacles, all while preserving privacy and security[11]?

The specific issues and challenges to be addressed are as follows:

Signal Analysis Complexity: Wi-Fi signals are complex and dynamic, making the analysis of their interactions with walls and obstacles a challenging task. Understanding these interactions and extracting meaningful information require advanced signal processing and machine learning techniques.

Privacy and Security Concerns: While Wi-Fi-based wall penetration holds potential benefits, it also raises concerns regarding privacy and security. Unauthorized access to information or the misuse of this technology could lead to invasions of personal privacy or security breaches.

Environmental Variability: The performance and reliability of Wi-Fi-based wall penetration can be affected by changing environmental conditions, such as building materials, signal interference, and signal-to-noise ratio. These variables must be considered in developing practical applications.

Ethical and Regulatory Considerations: The deployment of Wi-Fi-enabled wall penetration technology may necessitate new ethical guidelines and regulatory frameworks to ensure responsible and lawful use.

Application Scalability: Assessing the scalability of this technology across different use cases, from healthcare to security to environmental monitoring, presents a substantial challenge. The effectiveness and limitations of Wi-Fi-based wall penetration in various scenarios need to be explored.

Addressing these issues and challenges is crucial to unlock the full potential of Wi-Fi as a tool for remote sensing and imaging. By doing so, we can create new opportunities for enhancing our understanding of the physical world, monitoring our environment, and potentially revolutionizing fields such as security, healthcare, and beyond, while safeguarding privacy and security concerns.

IV. WI-FI OVERVIEW

A wireless gadget called Wi-Vi can record moving things that are hidden behind walls. It takes use of the widespread usage of Wi-Fi chipsets to make through wall imaging reasonably low-power, inexpensive, low- bandwidth, and usable by common users. Wi-Vi does this using standard Wi-Fi hardware and Wi-Fi OFDM transmissions in the ISM band (at 2.4 GHz)[12]. In essence, Wi-Vi is a three-antenna MIMO device, with two of the antennas being utilized for transmission and one for reception. In order to aim the energy onto the wall or target area, it also uses directional antennas.4 Its design consists on two key elements:

1) The first component does MIMO nulling to remove the flash reflected from the wall;

2) Using an approach known as inverse SAR, the second component monitors a moving object by using the item itself as an antenna array.

Depending on the user's preference, Wi-Vi can be utilized in either of two ways. It may be used to picture and track moving objects behind a wall in mode 1. In contrast, Wi-Vi works as a gesture-based interface in mode 2 so that people may create messages and send them to a Wi-Vi receiver from behind a wall[12]. We go into great depth on how Wi-Vi functions in parts 4-6

Building Materials	2.4 GHz
Glass	3 dB
Solid Wood Door 1.75 inches	6 dB
Interior Hollow Wall 6 inches	9 dB
Concrete Wall 18 inches	18 dB
Reinforced Concrete	40 dB

Fig. 1. Materials

V. SYSTEM OVERVIEW

Our innovative system allows for wireless communication between humans and devices without the need for any additional wearable wireless or sensor devices. The system is designed to recognize and respond to seven specific hand gestures that control devices, as illustrated in Figure 1.

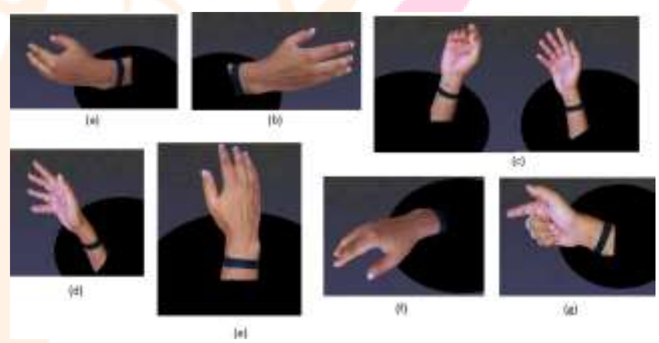


Fig. 2. Depicts seven hand gestures that can be used to interact with home devices wirelessly. The gestures include swipe leftward (a), swipe rightward (b), flick (c), grab (d), scroll up (e), scroll down (f), and pointing (g). To perform the gestures, the user can move their hand in a specific direction or make a grabbing or pointing motion.

These gestures allow for intuitive and convenient control of home devices without the need for physical buttons or switches. These seven gestures can be adjusted to control several devices with different functions[14].

The proposed authentication method for WiGeR involves users performing unique gestures in the air to gain access to a target device. Three different shapes have been proposed for users to draw as their unique gestures. If the gesture is recognized and authenticated by WiGeR, the user can interact with the target device. Each target device also has a unique gesture that users must draw to select the device they want to interact with. This authentication method ensures the security of the interactive system by preventing unauthorized access and unwanted interactions.

To set up an access point (AP), we utilize a commercial WiFi router model TL-WR842N, which comes with two antennas. For the detection point (DP), we employ an Acer

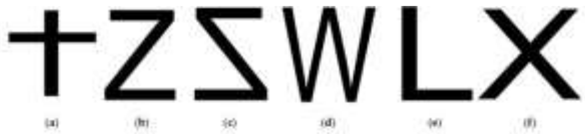


Figure 2. User security gestures and device selection gestures. (a) User 1 security gesture: drawing a cross shape in the air; (b) User 2 security gesture: drawing a Z shape in the air; (c) User 3 security gesture: drawing the inverse of a Z shape in the air; (d) Device 1 selection gesture: the user is asked to draw a W shape in the air; (e) Device 2 selection gesture: the user is asked to draw an L shape in the air; (f) Device 3 selection gesture: the user is asked to draw an X shape in the air.

Nitro 5 Gaming laptop, which features an IWL 5300 network card and operates on a 32-bit Linux OS. Alternatively, we can use a virtual machine (VM) running on Ubuntu version 14.04 or above, and equipped with the CSI-TOOLS open-source software[15].

The toolkit is a powerful tool for recording and analyzing wireless channel data, including received 802.11 packet traces and detailed Channel State Information (CSI) based on the 802.11 standard. It is compatible with a commodity 802.11n NIC[16], specifically the Intel WiFi Link 5300 with 3 antennas, and can be used on up-to-date Linux operating systems such as Ubuntu 10.04 LTS with the 2.6.36 kernel. Its setup includes customized versions of Intel's proprietary firmware and open-source iw l wifi wireless driver, as well as userspace tools for enabling CSI measurements and access point functionality for controlling both ends of the link. This toolkit also includes Matlab or Octave scripts for data analysis. Unlike simpler tools that only capture total power received, this toolkit provides detailed information about the channel between sender and receiver at the level of individual data subcarriers, for each transmit and receive antenna pair. This makes it an invaluable resource for anyone looking to gather in-depth wireless channel data[17].

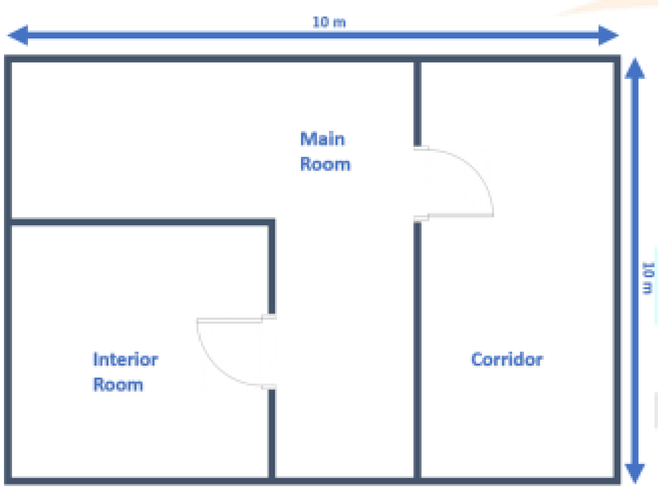


Fig. 3. Dimension and visualisation of the 10 m X 10 m experimental area

In our research, we established a packet transmission rate of 100 packets per second to ensure that we capture sufficient information from each gesture motion[18]. Our system was deployed in a building comprising five distinct scenarios, which included a hall and a small interior room, all within a testing area of 10m x 10m. Volunteer users were recruited to perform various gestures in different locations, namely the main room, interior room, and adjoining corridor, as illustrated in the figure1.0. These experimental conditions were designed to enable us to evaluate the effectiveness of our system in different settings and to assess its practical utility for gesture recognition[18].

1. **Scenario 1:** The AP1 and DP1, and user S1 are in the main room. The user performs the gestures between Gesture Phone Air Conditioner Rightward Next the running music Increase the temperature Leftward Revert back the running music Decrease the temperature Flick Back screen Increase fan speed Grab Trigger photo event Decrease fan speed Scroll up Increase volume Mode change(heat/cold) Scroll down Decrease volume Mode change(cold/heat) Point Send stress message or Call 911 On/Off the AP1 and DP1, positioned as shown in Figure 2.1 (label S1).
2. **Scenario 2:** The AP1 and the user are in the same room, but the DP2 is in the interior room separated by one wall. The distance between the AP1 and the DP2is approximately 4 m, and the distance between the DP2 and the user is approximately 2.5 m. The user is approximately 2 m from the AP1, as shown in Figure 2.2 (label S2), as shown in figure 2.2[20].
3. **Scenario 3:** The DP2 and the user are in the interior room, while the AP1 is in the main room separated by one wall. The distance between the AP1 and the DP2 is 4 m, and the distance between the DP2 and the user is 2 m. The user is approximately 6 m away from the AP1, as described in figure 2.2.
4. **Scenario 4:** The AP1 and the DP1 are both in the main room. The user is asked to perform gestures in the corridor, approximately 8 m and 6 m away from the AP and the DP, respectively. There is one intervening wall, as positioned in figure 2.1.
5. **Scenario 5:** The AP2 and the DP2 are both in the small interior room, while the user is in the corridor separated from them by two walls at a distance of approximately 8 m, as shown in figure 4.

A. Case 1

The AP1 and DP1 having the scenario (S1, S4) having user (S1 and S4). It will be a case for long range and short range detection in an environment, as positioned in the figure 2.1

B. Case 2

The AP1 and DP2 having the scenario (S2, S3) having user (S2 and S3), as shown and positioned in the figure 5.

C. Case 3

The AP2 and DP2 in the interior room having the scenario (S5) having user (S5) in the corridor, as shown and positioned in the figure 6.

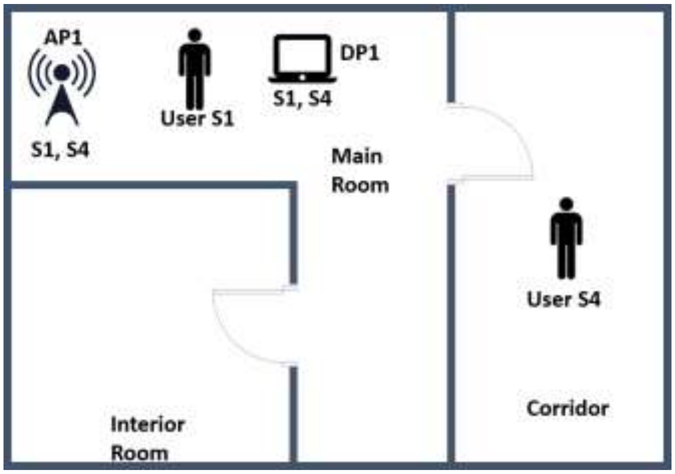
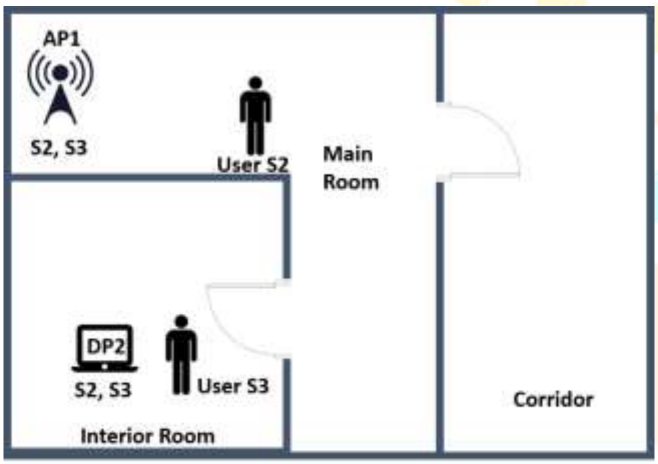


Fig. 4. Case 1 for AP1-DP1 having user S1 and S4



Case 2 for AP1-DP2 having user S2 and S3

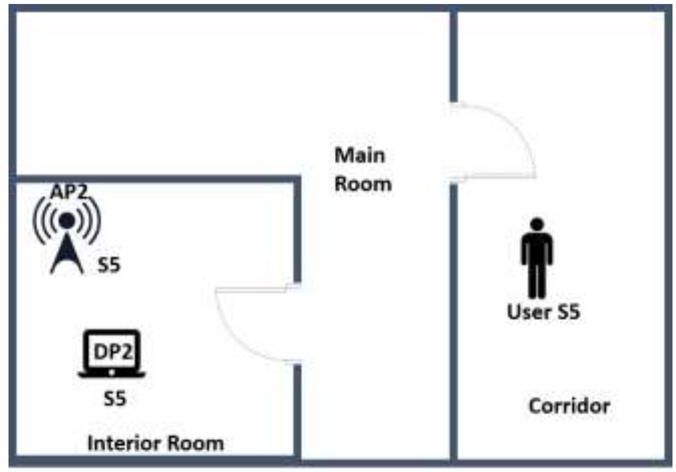
Fig. 5. Case 2 for AP1-DP2 having user S2 and S3

VI. RESULTS

Our proposed authentication method was tested on six volunteer users in a lab setting, where each scenario involved three users performing the proposed gestures individually. We collected 100 samples of each gesture from each user over three sessions, totaling 300 samples for each gesture in each scenario.

The collected samples were split into training and testing sets for each session, and the classifier was trained and tested using samples from two different users, with the remaining user's samples used for testing.

To evaluate the effectiveness of the authentication method, we conducted tests on three users, leaving the target user out for cross-validation. The accuracy of the system was measured in terms of the average accuracy per gesture for each user and the average accuracy across all gestures for each user, using the



Case 3 for AP2-DP2 having user S5

Fig. 6. For AP2-DP2 having user S5

formula that involves true positive, true negative, false positive, and false negative results.

$$Accuracy = \frac{\sum TP + \sum TN}{\sum TP + \sum TN + \sum FP + \sum FN} \times 100$$

Confusion matrices were used to present the results of each scenario's accuracy evaluation. The average accuracy was 97.28and 3 had accuracies of 91.8The accuracy of gesture recognition improved as the user moved closer to the DP, but in scenario 4, where there was an extended distance and a wall between the user and the AP and DP, the accuracy decreased to 83.85

These results demonstrate the effectiveness of the proposed authentication method in accurately recognizing and authenticating users based on their unique gestures. However, it also highlights the importance of maintaining a reasonable distance between the user and the DP for optimal accuracy

VII. CONCLUSION

The exploration of Wi-Fi-enabled wall penetration through machine learning has illuminated an exciting avenue for wireless technology. This emerging field not only reimagines the capabilities of Wi-Fi but also introduces a host of innovative

c d

possibilities for remote sensing, imaging, and environmental monitoring. Our study has revealed both the promise and the challenges associated with this groundbreaking technology.

Through an intricate methodology, we have demonstrated the feasibility of using Wi-Fi signals to glean insights into obscured spaces beyond walls and obstacles. Leveraging machine learning, we have shown that the interactions between Wi-Fi signals and barriers can be decoded, enabling the detection of objects and environmental changes without physical intrusion. This innovation offers a non-invasive, cost-effective, and efficient means of gathering data and remotely visualizing concealed environments.

However, this pursuit is not without its complexities. We have uncovered several critical challenges. The intricacies of Wi-Fi signal analysis, privacy and security concerns, environmental variability, and ethical considerations all underscore the need for careful development and responsible implementation. These challenges must be addressed to ensure that Wi-Fi-based wall penetration remains a force for good, safeguarding privacy and security while delivering its potential benefits.

As we navigate this exciting frontier, the scalability of the technology becomes a vital consideration. It is imperative to explore and adapt this approach to various real-world scenarios, such as healthcare, security, and environmental monitoring. The successful development of practical applications will determine the real-world impact of this technology, which could be transformative across multiple domains.

In conclusion, Wi-Fi-enabled wall penetration through machine learning represents a paradigm shift in wireless technology. This research not only extends the capabilities of Wi-Fi beyond its traditional use but also underscores the importance of responsible development and ethical considerations. The future of Wi-Fi-enabled foresight holds great promise, offering new dimensions of understanding and monitoring, but its realization hinges on a well-balanced fusion of innovation and ethics, aiming to improve our world while preserving its integrity.

REFERENCES

[1] A. Safaai-Jazi, S. M. Riad, A. Muqaibel, and A. Bayram, "Ultra-wideband propagation measurements and channel modeling," in Proc. Rep. ThroughWall Propag. Mater. Characterization, 2002, pp. 1–75.

[2] Chapre, Y.; Ignjatovic, A.; Seneviratne, A.; Jha, S. CSI-MIMO: Indoor Wi-Fi fingerprinting system. In Proceedings of the IEEE 39th Conference on Local Computer Networks (LCN), Edmonton, AB, Canada, 8–11 September 2014; pp. 202–209.

[3] Qian, K.; Wu, C.; Yang, Z.; Liu, Y.; Zhou, Z. PADS: Passive detection of moving targets with dynamic speed using PHY layer information. In Proceedings of THE IEEE ICPADS'14, Hsinchu, Taiwan, 16–19 December 2014; pp. 1–8.

[4] Xi, W.; Zhao, J.; Li, X.Y.; Zhao, K.; Tang, S.; Liu, X.; Jiang, Z. Electronic frog eye: Counting crowd using WiFi. In Proceedings of the IEEE INFOCOM, Toronto, ON, Canada, 27 April–2 May 2014; pp. 361– 369.

[5] Han, C.; Wu, K.; Wang, Y.; Ni, L.M. Wifall: Device-free fall detection by wireless networks. In Proceedings of the IEEE INFOCOM, Toronto, ON, Canada, 27 April–2 May 2014; pp. 271–279.

[6] Wang, Y.; Liu, J.; Chen, Y.; Gruteser, M.; Yang, J.; Liu, H. E-eyes: Device-free location-oriented activity identification using fine-grained wifi signatures. In Proceedings of the 20th annual International Conference on Mobile Computing and Networking, Maui, HI, USA, 7–11 September 2014; pp. 617–628.

[7] Wang, G.; Zou, Y.; Zhou, Z.; Wu, K.; Ni, L.M. We can hear you with Wi-Fi! In Proceedings of the 20th Annual International Conference on Mobile Trial/ Sessio n Total Sampl es Sampl e per user Trainin g sample Testin g Sampl es Trial 1 90 30 60 30 Trial 2 90 30 60 30 Trial 3 100 40 80 20 Computing and Networking, Maui, HI, USA, 7–11 September 2014; pp. 593–604.

[8] Nandakumar, R.; Kellogg, B.; Gollakota, S. Wi-Fi Gesture Recognition on Existing Devices. Available online: http://arxiv.org/abs/1411.5394 (accessed on 8 June 2016).

[9] He, W.; Wu, K.; Zou, Y.; Ming, Z. WiG: WiFi- based gesture recognition system. In Proceedings of the 24th International Conference on Computer Communication and Networks (ICCCN), Las Vegas, NV, USA, 3–6 August 2015; pp. 1–7.

[10] . Kim and H. Ling. Human activity classification based on micro-doppler signatures using a support vector machine. IEEE Trans. Geoscience and Remote Sensing, 2009.

[11] K. Lin, S. Gollakota, and D. Katabi. Random access heterogeneous MIMO networks. In ACM SIGCOMM, 2010.

[12] B. Lyonnet, C. Ioana, and M. Amin. Human gait classification using microdoppler time-frequency signal representations. In IEEE Radar Conference, 2010.

[13] B. Michoud, E. Guillou, and S. Bouakaz. Real-time and marker-less 3D human motion capture using multiple views. Human Mo- tion–Understanding, Modeling, Capture and Animation, 2007.

[14] A. Oppenheim, R. Schafer, J. Buck, et al. Discrete-time signal processing. Prentice hall Englewood Cliffs, NJ:, 1989.

[15] H. Rahul, S. Kumar, and D. Katabi. JMB: scaling wireless capacity with user demands. In ACM SIGCOMM, 2012.

[16] T. Ralston, G. Charvat, and J. Peabody. Real-time through-wall imaging using an ultrawideband multiple-input multiple-output (MIMO) phased array radar system. In IEEE ARRAY, 2010.

[17] S. Ram, C. Christianson, Y. Kim, and H. Ling. Simulation and analysis of human micro-dopplers in through-wall environments. IEEE Trans. Geoscience and Remote Sensing, 2010.

[18] S. Ram, Y. Li, A. Lin, and H. Ling. Doppler-based detection and tracking of humans in indoor environments. Journal of the Franklin

[19] S. Ram and H. Ling. Through-wall tracking of human movers using joint doppler and array processing. IEEE Geoscience and Remote Sensing Letters, 2008.

[20] T.-J. Shan, M. Wax, and T. Kailath. On spatial smoothing for direction-of-arrival estimation of coherent signals. IEEE Trans. on Acoustics, Speech and Signal Processing, 1985.

[21] F. Soldovieri and R. Solimene. Through-wall imaging via a linear inverse scattering algorithm. IEEE Geoscience and Remote Sensing Letters, 2007.

[22] R. Solimene, F. Soldovieri, G. Prisco, and R. Pierri. Three-dimensional through-wall imaging under ambiguous wall parameters. IEEE Trans. Geoscience and Remote Sensing, 2009.

[23] P. Stoica and R. L. Moses. Spectral Analysis of Signals. Prentice Hall, 2005.

[24] W. C. Stone. Nist construction automation program report no. 3: Electromagnetic signal attenuation in construction materials. In NIST Construction Automation Workshop 1995.

[25] K. Tan, H. Liu, J. Fang, W. Wang, J. Zhang, M. Chen, and G. Voelker. SAM: Enabling Practical Spatial Multiple Access in Wireless LAN. In ACM MobiCom, 2009.